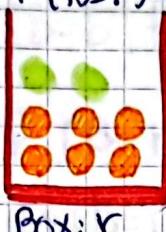


# Ejercicios Probabilidades.

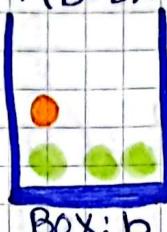
Priors:

$$P(B=r) = 0,4$$



Box: r

$$P(B=b) = 0,6$$



Box: b

● : Apple

○ : Orange

B : Box (Blue, Red) : b, r

$$B \in \{r, b\}$$

F: fruit (apple or Orange) : a, o

$$F \in \{a, o\}$$

Ejercicios

$$\bullet P(B=r) = 0,4 = \frac{4}{10}$$

$$\bullet P(B=b) = 0,6 = \frac{6}{10}$$

$$\bullet P(f=a | B=r) = \frac{2}{8} = \frac{1}{4} \rightarrow (\text{Me voy a la caja roja y miro sus elementos})$$

$$\bullet P(f=a | B=b) = \frac{3}{4}$$

$$\bullet P(f=o | B=r) = \frac{6}{8} = \frac{3}{4}$$

$$\bullet P(f=o | B=b) = \frac{1}{4}$$

$$\bullet P(f=a) = \sum_{B:r,b} P(F=a, B=B_j) \rightarrow \text{Regla de la Suma.}$$

Como no tenemos la conjunta vamos a expresarla en términos de las condicionales esto lo podemos expresar con la Regla del producto entonces:

$$P(f=a) = P(f=a | B=r) P(B=r) + P(f=a | B=b) P(B=b)$$

$$P(f=a) = \frac{1}{4} \cdot \frac{4}{10} + \frac{3}{4} \cdot \frac{6}{10} = \frac{4}{40} + \frac{18}{40} = \frac{22}{40} = \frac{11}{20}$$

$$P(f=a) = \frac{1}{10} + \frac{9}{20} = \frac{20+90}{200} = \frac{110}{200} = \frac{11}{20}$$

$$P(f=a) = \frac{11}{20}$$

$$\cdot P(F=O) = \frac{9}{20}$$

$$P(f=a) + P(f=O) = 1$$

$$P(f=O) = 1 - P(f=a)$$

$$P(f=O) = 1 - \frac{11}{20}$$

$$P(f=O) = \frac{20-11}{20} = \frac{9}{20}$$

$$P(f=O) = \frac{9}{20}$$

$$\cdot P(B=r | f=O) = \frac{2}{3}$$

Esto lo solucionamos por Bayes ya que podemos despejarlo a partir de la probabilidad de que ocurra  $P(f=O | B=r)$ , entonces tenemos que:

$$P(B=r | f=O) = \frac{P(f=O | B=r) \cdot P(B=r)}{P(f=O)}$$

$$P(B=r | f=O) = \frac{(3/4)(4/10)}{(9/20)} = \frac{12/40}{9/20} = \frac{12}{9} = \frac{4}{3}$$

$$P(B=r | f=O) = \frac{12 \cdot 20}{9 \cdot 40} = \frac{4}{3} \cdot \frac{2}{4} = \frac{8}{12} = \frac{2}{3}$$

$$P(B=r | f=O) = \frac{2}{3}$$

$$\cdot P(B=b | f=O) = \frac{1}{3}$$

$$P(B=b | f=O) = \frac{P(f=O | B=b) \cdot P(B=b)}{P(f=O)}$$

$$P(B=b | f=O) = \frac{(1/4)(6/10)}{(9/20)} = \frac{6/40}{9/20} = \frac{6}{40} = \frac{6 \cdot 20}{9 \cdot 40}$$

$$P(B=b | f=0) = \frac{12}{36} = \frac{1}{3}$$

$$P(B=b | f=1) = \frac{1}{3}$$

$$\cdot P(B=r | f=0) = 2/11$$

$$P(B=r | f=1) = \frac{P(f=1 | B=r) P(B=r)}{P(f=1)}$$

$$P(B=r | f=1) = \frac{(1/4)(4/10)}{(11/20)}$$

$$P(B=r | f=1) = \frac{(4/40)}{(11/20)} = \frac{\frac{4}{40}}{\frac{11}{20}} = \frac{4/20}{11/20} = \frac{2}{11}$$

$$P(B=r | f=1) = \frac{2}{11}$$

$$\cdot P(B=b | f=1) = \frac{9}{11}$$

$$P(B=b | f=1) = \frac{P(f=1 | B=b) P(B=b)}{P(f=1)} = \frac{(3/4)(6/10)}{(11/20)}$$

$$P(B=b | f=1) = \frac{18}{40}, \frac{18/11}{20} = \frac{9}{11}$$

$$(V-X)(V+X) = V^2 - X^2$$

$$(V-X)(V+X) = V^2 - X^2$$

$$(x_1 - x_2)(x_1 + x_2) = x_1^2 - x_2^2$$

$$x_1^2 - x_2^2$$

## Tareas TAM. PRIMER CORTE.

TAM

→ Demostaciones

$$\rightarrow \text{Var}\{x\} = E\{x^2\} - E^2\{x\}$$

$$\text{Var}\{x\} = E\{x^2\} - E^2\{x\}$$

$$= E\{(x - \mu_x)^2\}$$

$$= E\{x^2 - 2x\mu_x + \mu_x^2\}$$

$$= E\{x^2\} - 2E\{x\}E\{x\} + E\{\mu_x^2\}$$

$$= E\{x^2\} - 2E\{x\}E\{x\} + \mu_x^2$$

$$= E\{x^2\} - 2E^2\{x\} + E^2\{x\}$$

$$= E\{x^2\} - E^2\{x\}$$

Nota:  $E\{x\} = \mu_x$

$$\rightarrow \text{COV}\{x, y\} = E_{xy}\{xy\} - E\{x\}E\{y\}$$

$$\text{COV}\{x, y\} = E_{xy}\{xy\} - E\{x\}E\{y\}$$

$$\text{COV}\{x, y\} = E_{xy}\{$$

$$= E_{x,y}\{xy - \mu_x y - x\mu_y + \mu_x \mu_y\}$$

$$= E_{x,y}\{xy\} - \mu_x E\{y\} - E\{x\}\mu_y + \mu_x \mu_y$$

$$= E_{x,y}\{xy\} - E\{x\}E\{y\} - E\{x\}E\{y\} + E\{x\}E\{y\}$$

$$= E_{x,y}\{xy\} - E\{x\}E\{y\}$$

Nota:  $E\{x\} = \mu_x$

TAM.

## Demostraciones

$$\rightarrow \text{COV}\{x, y\} = E\{xy\} - E\{x\}E\{y\}$$

$$\begin{aligned}
 \text{COV}\{x, y\} &= E\{xy\} - E\{x\}E\{y\} \\
 &= E\{x, y^T\} - E\{x\}E\{y^T\} \\
 &= E\{x, y\} - E\{x\}E\{y^T\} - E\{y^T\}E\{x\} + E\{x\}E\{y^T\} \\
 &= E\{x, y\} - E\{x\}E\{y^T\} - E\{x\}E\{y^T\} + E\{x\}E\{y^T\} \\
 &= E\{x, y\} - E\{x\}E\{y^T\}.
 \end{aligned}$$

$$E\{x\} = \int_{-\infty}^{\infty} N(x | \mu, \sigma^2) x dx = \mu$$

$$E\{x\} = \int_{-\infty}^{\infty} N(x | \mu, \sigma^2) x dx = \mu$$

$$E\{x\} = \int_{-\infty}^{\infty} N(x | \mu, \sigma^2) x dx$$

$$= \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{|x-\mu|^2}{2\sigma^2}\right) x dx.$$

sustituimos  $z = x - \mu$ ,  
 $dz = dx$ .

$$E\{x\} = \int_{-\infty}^{\infty} \frac{(z+\mu)}{\sqrt{2\pi\sigma^2}} \cdot \exp\left(-\frac{|z|^2}{2\sigma^2}\right) dz.$$

$$\begin{aligned}
 &= \underbrace{\int_{-\infty}^{\infty} \frac{z}{\sqrt{2\pi\sigma^2}} \cdot \exp\left(-\frac{|z|^2}{2\sigma^2}\right) dz}_{\text{impar}} + \mu \underbrace{\int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi\sigma^2}} \cdot \exp\left(-\frac{|z|^2}{2\sigma^2}\right) dz}_{\text{par}}.
 \end{aligned}$$

$$\int_{-\infty}^{\infty} N(x | \mu, \sigma^2) dx = 1.$$

$$E\{x\} = \mu$$

TAM.

## Demostraciones

$$\rightarrow \mathbb{E}\{x^2\} = \int_{-\infty}^{\infty} N(x|\mu, \sigma^2) x^2 dx = \mu^2 + \sigma^2$$

$$\mathbb{E}\{x^2\} = \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi\sigma^2}} \cdot \exp\left(-\frac{|x-\mu|^2}{2\sigma^2}\right) x^2 dx.$$

Reemplazamos  $z = x - \mu$ ,  $dz = dx$ .

$$\mathbb{E}\{x^2\} = \int_{-\infty}^{\infty} \frac{(z+\mu)^2}{\sqrt{2\pi\sigma^2}} \cdot \exp\left(-\frac{|z|^2}{2\sigma^2}\right) dz.$$

$$\begin{aligned} \mathbb{E}\{x^2\} &= \int_{-\infty}^{\infty} \frac{z^2}{\sqrt{2\pi\sigma^2}} \cdot \exp\left(-\frac{|z|^2}{2\sigma^2}\right) dz + \mu \int_{-\infty}^{\infty} \frac{z}{\sqrt{2\pi\sigma^2}} \cdot \exp\left(-\frac{|z|^2}{2\sigma^2}\right) dz \\ &\quad + \mu^2 \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi\sigma^2}} \cdot \exp\left(-\frac{|z|^2}{2\sigma^2}\right) dz \end{aligned}$$

$$\boxed{\mathbb{E}\{x^2\} = \sigma^2 + \mu^2}$$

$$\boxed{\text{Var}\{x\} = \sigma^2}$$

$$\text{Var}\{x\} = \sigma^2$$

$$\begin{aligned} \text{Var}\{x\} &= \mathbb{E}\{x^2\} - \mathbb{E}^2\{x\} \\ &= \sigma^2 + \mu^2 - \mu^2. \end{aligned}$$

$$\boxed{\text{Var}\{x\} = \sigma^2}$$

## Demostraciones

TAM

$$M_{ML} = \arg \max_{\mu} \log(P(x))$$

$$\frac{d \log(P(x))}{d \mu} = 0$$

$$\frac{d}{d \mu} \left( -\frac{N}{2} \log(2\pi) \right) - \frac{d}{d \mu} \left( \frac{N}{2} \log(\sigma^2) \right) - \frac{d}{d \mu} \left( \frac{1}{2\sigma^2} \sum_{n=1}^N |x_n - \mu|^2 \right) = 0$$

$$\frac{d}{d \mu} \left( \frac{1}{2\sigma^2} \sum_{n=1}^N |x_n - \mu|^2 \right) = 0.$$

$$\frac{1}{2\sigma^2} \cdot \sum_{n=1}^N \left( \frac{d}{d \mu} |x_n - \mu|^2 \right) = 0$$

$$\frac{1}{2\sigma^2} \sum_{n=1}^N 2(x_n - \mu)(-1) = 0$$

$$\sum_{n=1}^N x_n - \sum_{n=1}^N \mu = 0$$

$$N \cdot \mu = \sum_{n=1}^N x_n$$

$$M_{ML} = \frac{1}{N} \sum_{n=1}^N x_n \rightarrow \text{estimador de media muestral}$$

## → Demarcaciones

TAM.

$$\rightarrow \hat{\sigma}_{ML}^2 = \arg \max_{\sigma^2} \log(P(x))$$

$$\frac{d}{d\sigma} (\log(P(x))) = 0$$

$$\frac{d}{d\sigma} \left( -\frac{N}{2} \log(2\pi) \right) - \frac{d}{d\sigma} \left( \frac{N}{2} \log(\sigma^2) \right) - \frac{d}{d\sigma} \left( \frac{1}{2\sigma^2} \sum_{n=1}^N |x_n - M|^2 \right) = 0$$

$$\frac{N}{2} \cdot \frac{d}{d\sigma} (2 \log(\sigma)) + \frac{1}{2} \frac{d}{d\sigma} \left( \frac{1}{\sigma^2} \right) \sum_{n=1}^N |x_n - M|^2 = 0.$$

$$\frac{N}{\sigma} + \frac{1}{2} \cdot -2 \cdot \sum_{n=1}^N |x_n - M|^2 = 0.$$

$$\sqrt{3} \left( \frac{N}{\sigma} \right) + \sqrt{3} \left( \frac{1}{2} \cdot -2 \cdot \sum_{n=1}^N |x_n - M|^2 \right) = 0$$

$$N\sigma^2 - \sum_{n=1}^N |x_n - M|^2 = 0$$

$$\boxed{\hat{\sigma}_{ML}^2 = \frac{1}{N} \sum_{n=1}^N |x_n - M|_L^2}$$

→ Demonstraciones

Busqueda del mejor estimador

$$A_1 = \frac{1}{N} \sum_{n=1}^N x_n ; A_2 = \bar{x}$$

$$\rightarrow ecm(\theta, \hat{\theta}) = \text{Var}\{\hat{\theta}\} + b^2 f(\theta); A_1 \text{ vs } A_2$$

$$\bullet b(A_1) = E\{A_1\} - A$$

$$= \frac{1}{N} \sum_{n=1}^N E\{x_n\} - A$$

$$= \frac{1}{N} \sum_{n=1}^N E\{A + w_n\} - A.$$

$$= \frac{1}{N} \sum_{n=1}^N A - A$$

$$= A - A = 0$$

$$\bullet b(A_2) = E\{A_2\} - A = E\{x\} - A = A - A = 0$$

$$\bullet \text{Var}\{A_1\} = \text{Var}\left\{ \frac{1}{N} \sum_{n=1}^N (A + w_n) \right\} ; \text{Var}\{A_2\} = \text{Var}\{x\}$$

$$= \text{Var}\left\{ \frac{1}{N} \sum_{n=1}^N A + \frac{1}{N} \sum_{n=1}^N w_n \right\}$$

$$= \text{Var}\{A + w\}$$

$$= \text{Var}\left\{ \frac{1}{N} \sum_{n=1}^N w_n \right\}$$

$$\boxed{\text{Var}\{A_2\} = \sigma^2}$$

$$= \sum_{n=1}^N \text{Var}\left\{ \frac{1}{N} w_n \right\}$$

$$= \sum_{n=1}^N \frac{1}{N^2} \sigma^2$$

$$\boxed{\text{Var}\{A_1\} = \frac{\sigma^2}{N}}$$

→ Mejor estimador.

$$A_1 = \frac{1}{N} \sum_{n=1}^N x_n$$

Bogos

Varianzas

## Demostraciones

TAM

$$\rightarrow \mathbb{E}\{\bar{M}_{ML}\} = \mathbb{E}\left\{\frac{1}{N} \sum_{n=1}^N x_n\right\} (= M)$$

$$\begin{aligned}\mathbb{E}\{\bar{M}_{ML}\} &= \frac{1}{N} \sum_{n=1}^N \mathbb{E}\{x_n\} \\ &= \frac{1}{N} \sum_{n=1}^N M \\ &= \frac{1}{N} \cdot N \cdot M\end{aligned}$$

$$\boxed{\mathbb{E}\{\bar{M}_{ML}\} = M}$$

$$\rightarrow \mathbb{E}\{\bar{S}_{ML}^2\} = \mathbb{E}\left\{\frac{1}{N} \sum_{n=1}^N |x_n - M|_L^2\right\} (= \frac{(N-1)}{N} \bar{S}^2)$$

$$\begin{aligned}\mathbb{E}\{\bar{S}_{ML}^2\} &= \mathbb{E}\left\{\frac{1}{N} \sum_{n=1}^N |x_n - M|_L^2\right\} \\ &= \frac{1}{N} \sum_{n=1}^N (\mathbb{E}(x_n^2) - 2\mathbb{E}\{x_n\} \mathbb{E}\{\bar{M}_{ML}\} + \mathbb{E}\{\bar{M}_{ML}^2\}). \\ &= \frac{1}{N} \sum_{n=1}^N (\bar{S}^2 + M^2 - \mathbb{E}\{\bar{M}_{ML}^2\})\end{aligned}$$

Así,

$$\begin{aligned}\mathbb{E}\{\bar{M}_{ML}^2\} &= \mathbb{E}\{\bar{M}_N^2\} - \mathbb{E}^2\{\bar{M}_{ML}\} \\ \mathbb{E}\{\bar{S}_{ML}^2\} &= \text{Var}\{\bar{M}_{ML}\} + \mathbb{E}^2\{\bar{M}_{ML}\}. \\ &= \text{Var}\left\{\frac{1}{N} \sum_{n=1}^N x_n\right\} + M^2 \\ &= \frac{1}{N^2} \cdot N \bar{S}^2 + M^2 \\ &= \frac{1}{N} \bar{S}^2 + M^2.\end{aligned}$$

$$\begin{aligned}\mathbb{E}\{\bar{S}_{ML}^2\} &= \frac{1}{N} \sum_{n=1}^N (\bar{S}^2 + M^2 - \frac{M^2}{n}) \\ &= \frac{1}{N} \cdot N \bar{S}^2 \left(1 - \frac{1}{N}\right)\end{aligned}$$

$$\boxed{\mathbb{E}\{\bar{S}_{ML}^2\} = \frac{N-1}{N} \bar{S}^2}$$

TAM.

## Demostraciones

$$\Sigma^2 = \Delta$$

$$(M - \mu I) \text{ and } M^T = M$$

$$(M - \mu I)^T = M^T - \mu I =$$

$$\Phi^T \Phi = V \Delta V^*$$

$$(M - \mu I)^T = M^T - \mu I =$$

$$(V S V^*)^T (V S V^*) = V \Delta V^*$$

$$(V^*)^T \underbrace{S^T U^T}_{I} U S V^* = V \Delta V^*$$

$$V S^T S V^* = V \Delta V^*$$

$$V S^2 V^* = V \Delta V^*$$

Por lo tanto,  $\Sigma^2 = \Delta$ .

$$\begin{aligned}\Phi^T \Phi &= V \Delta V^* \\ \Phi_{\text{proj}} &= V S V \\ U^T U &= I \\ V^T V &= I\end{aligned}$$

$$\lambda_{ab} = \lambda_a + \Sigma_{ab} \Sigma_{bb}^{-1} (\lambda_b - \lambda_b)$$

$$\Sigma_{ab} = \Sigma_{aa} - \Sigma_{ab} \Sigma_{bb}^{-1} \Sigma_{ba}$$

①

Identidad de la matriz inversa por partes

$$\begin{bmatrix} A & B \\ C & D \end{bmatrix}^{-1} = \begin{bmatrix} M & -MBD^{-1} \\ -DCM & D^{-1} + D^{-1}CMBD^{-1} \end{bmatrix}$$

$$\text{Siendo } M = (A - BD^{-1}C)^{-1}$$

$$\begin{bmatrix} \Delta_{aa} & \Delta_{ab} \\ \Delta_{ba} & \Delta_{bb} \end{bmatrix} = \begin{bmatrix} \Sigma_{aa} & \Sigma_{ab} \\ \Sigma_{ba} & \Sigma_{bb} \end{bmatrix}^{-1} = \begin{bmatrix} M & -M\Sigma_{ab}\Sigma_{bb}^{-1} \\ -\Sigma_{bb}\Sigma_{ba} & \Sigma_{bb}^{-1} + \Sigma_{bb}\Sigma_{ba}M\Sigma_{ab}\Sigma_{bb}^{-1} \end{bmatrix}$$

$$\text{donde } M = (\Sigma_{aa} - \Sigma_{ab}\Sigma_{bb}^{-1}\Sigma_{ba})^{-1}$$

$$\text{Así; } \Sigma_{ab} = \Delta_{aa}^{-1} = \Sigma_{aa} - \Sigma_{ab}\Sigma_{bb}^{-1}\Sigma_{ba}$$

MAT

(2)

$$M_{ab} = M_a - \sum_{ab} \lambda_{ab} (M_b - X_b)$$

$$= M_a - M^{-1} (-M \sum_{ab} \sum_{bb}^{-1}) (M_b - X_b)$$

$$= M_a + \sum_{ab} \sum_{bb}^{-1} (-M_b - X_b)$$

$$= M_a - \sum_{ab} \sum_{bb}^{-1} (X_b - M_b)$$

$$EVOL = (V_2 - V_1)^T P V_2$$

$$VAU = V_2 U V_2^T (V_2)$$

$$VUV = V_2 U V_2^T V_1$$

$$VAU = VU + V$$

$$VUV = \phi, A = 52, V_1 = 1, V_2 = 1$$

$$V_2 U = \phi$$

$$U V_2 = \phi$$

$$\vdash VUV$$

$$\vdash VUV$$

$$(M - \alpha I) \text{ adj } M^{-1} + \alpha I = M^{-1}$$

$$\text{adj } M^{-1} I + \alpha I = M^{-1}$$

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$$\begin{bmatrix} I & M \\ -A & I - AM \end{bmatrix} = \begin{bmatrix} B & A \\ C & D \end{bmatrix}$$

$$(I - B) = M \text{ adj } M$$

$$\text{adj } M \cdot M =$$

$$M \cdot$$

$$M =$$

$$\begin{bmatrix} \text{adj } M \cdot M \\ 0 \end{bmatrix} = \begin{bmatrix} \text{adj } M \cdot M \\ 0 \end{bmatrix}$$

$$3 \text{ adj } M \cdot M + 3 \text{ adj } M + 3$$

$$\begin{bmatrix} \text{adj } M \cdot M \\ 0 \end{bmatrix} = \begin{bmatrix} \text{adj } M \cdot M \\ 0 \end{bmatrix}$$

$$3 \text{ adj } M \cdot M + 3 \text{ adj } M + 3 = 1 \cdot M \quad \text{adj } M$$

$$3 \text{ adj } M \cdot M + 3 \text{ adj } M + 3 = 1 \cdot M \cdot M$$